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ABSTRACT

This study compares the abilities of statistical model forecasts versus financial analyst forecasts to serve as surrogates for market expectations of quarterly and annual earnings per share. For both annual and interim earnings expectations, statistical model forecast errors are found to be associated with risk adjusted security returns, even with financial analyst forecast errors held constant. Similarly, financial analyst forecast-errors are associated with security returns after controlling for statistical model forecast errors.

Additional tests are performed on the null hypothesis that the financial analysts exploit all information used by the time-series models. The data indicate rejection of this hypothesis for both annual and interim forecasts. Finally, forecast error analysis supports previous research in finding that analyst forecasts are more accurate than those of statistical models. However, this superiority disappears after controlling for hypothesized timing advantages favoring the analysts.

EVIDENCE ON SURROGATES FOR EARNINGS EXPECTATIONS WITHIN A CAPITAL MARKET CONTEXT

A substantial body of accounting research has relied on expectations or forecasts of earnings or earnings per share. This is especially true in the capital market/informational content area. Examples of such studies are those of Ball and Brown [1968], Beaver [1968], Beaver and Dukes [1972], Brown and Kennelly [1972], Joy et al. [1977] and Kiger [1972].

The importance of the choice of the forecast used in capital market research designs has been widely recognized. For example, Foster [1977, p. 2] wrote "choice of an inappropriate [forecast] model (one inconsistent with the time series) may lead to erroneous inferences about the information content of accounting data." This fact has contributed to motivating a large number of studies comparing accuracy of competing sources of earnings forecasts. Some have focused on the relative forecast accuracy of statistical models (e.g., Brown and Rozeff [1979], Griffin [1977], Lorek [1979] and Watts [1975]). Others have focused on forecast accuracy of financial analysts versus statistical models (e.g., Brown and Rozeff [1978] and Collins and Hopwood [1980]). These and other studies have provided evidence that the financial analysts provide expectations of earnings which are substantially more accurate than those generated by the statistical models examined thus far.

While information on forecast accuracy has, to a degree, served as a measure of the usefulness of a given source of forecasts, a number of researchers (e.g., Brown and Kennelly [1972], Foster [1977], Watts [1978] and Fried and Givoly [1982]) have noted that a more direct approach to evaluating a forecast source is to examine the association between its

forecast error and abnormal security returns. For example, Brown and Kennelly [1972, p. 104] write:

> This experimental design permits a direct comparison between alternative forecasting rules . . . The . . . contention is based on the hypothesis (and evidence) that the stock market is "both efficient and unbiased in that, if information is useful in forming capital asset prices, then the market will adjust asset prices to the information quickly and without leaving any opportunity for further abnormal gain" (Ball and Brown [1968]. There is, then a presumption that the consensus of the market reflects, at any point, an estimate of future EPS which is the best possible from generally available data. Since the abnormal rate of return measures the extent to which the market has reacted to errors in its previous expectations, <u>the abnormal rate of return can be used to assess the predictive accuracy of any device which attempts to forecast a number that is relevant to investors</u>. [Emphasis added]

Along these lines, Foster [1977] investigated several models for quarterly earnings and found that a model with both seasonal and non-seasonal components best represented the market expectation for earnings, where the "best expectation" was measured in terms of association between model error and risk adjusted returns. Using similar methods, Brown and Kennelly [1972] found that certain quarterly models generated better surrogates of capital market expectations than those generated from annual models.

Notwithstanding the fact that the utility of market-based approach has become widely known, there has been little previous research that has applied this methodology to the evaluation of financial analyst forecasts. Such an application seems highly desirable since previous research (e.g., Brown and Rozeff [1978] and Collins and Hopwood [1980]) has found that analysts generate forecasts which are more accurate than those of statistical models.

The purpose of the present study is therefore to further investigate the issue of financial analyst forecasts versus statistical model expectations within a capital market context. In particular, the objective is to evaluate the relative ability of financial analyst versus statistical model forecasts to surrogate for market expectations of earnings and to incorporate publicly available information. First, the association between risk adjusted security returns and the forecast errors of statistical models is compared to the association between risk adjusted security returns and forecast errors of financial analysts. Second, the association between the financial analyst forecast errors and risk adjusted security returns is evaluated, while holding constant statistical model forecast errors. Third, the association between the statistical model forecast errors and risk adjusted returns is evaluated, while holding constant financial analyst forecast errors.

The first of these 3 associations deals with the question as to which source of forecasts more closely approximates the market's expectation for earnings. The second and third associations deal with the question as to whether a given source of forecasts (i.e., analysts versus statistical models) <u>uniquely</u> surrogates for the market's expectation of earnings. Stated differently, issues two and three deal with the <u>incremental ability</u> of the analysts versus statistical models to explain risk adjusted returns. For example, statistical significance in the third case would indicate that the statistical model errors explain a portion of risk-adjusted returns that is not explained by the analyst forecast errors.

Next, tests are presented analogous to the market association tests described in the previous paragraph, but reported earnings are used as a

dependent variable in place of risk adjusted security returns. These tests therefore focus on the ability of the different forecast sources to explain reported earnings as opposed to market behavior. That is, they deal with the issue of the relative ability of the competing sources of forecasts to exploit the information available for purposes of forecasting reported earnings.

Finally, forecast accuracy results are presented in order to enhance comparability with previous research. In addition, consistent with our central objective of forecast evaluation, we also evaluate the hypothesis that the superior forecasting accuracy of financial analyst is due to a timing advantage.[1]

We note that there are many previous studies that have evaluated earnings forecasts. However, virtually all of these studies either did not include financial analyst forecasts or were not market-based. Inclusion of analyst forecasts is important since a number of studies have indicated that financial analyst forecasts are more accurate than those of statistical models.

One study that has included both analyst forecasts and market returns is that of Fried and Givoly [1982] who evaluated the association between risk adjusted security returns and annual earnings forecast errors of certain statistical models and financial analysts. The objectives of the present study differ from those of Fried and Givoly [1982] in two important ways. First, the FG study focused on annual earnings alone, whereas the present study investigates both annual and interim earnings forecasts. Second, the FG study did not address the question as to whether the financial analyst forecasts uniquely explain risk adjusted security returns. That is, the FG study didn't evaluate the

association between financial analyst forecast errors and risk adjusted security returns with the statistical model forecasts errors held constant. A number of other differences between the current research and the previous literature are discussed in a subsequent section of this paper.

The remainder of this paper consists of five sections. The first discusses the present study relative to previous research. Section two summarizes the eighteen statistical expectation models. Sections three and four give annual and quarterly forecast results, respectively. The last section includes a summary and conclusions.

THE PRESENT STUDY RELATIVE TO PREVIOUS RESEARCH

The present study can be distinguished from previous research in four broad areas: 1) the incorporation of financial analyst forecasts into the design, and the presentation of capital market results for forecast comparisons between analyst and statistical models for both interim and annual earnings forecasts; 2) specific methodological refinements; 3) a very broad set of statistical models (including multivariate time-series models and those that exploit interim data), and 4) it extends previous research by investigating the hypothesis that financial analyst forecast superiority over statistical models can be accounted for by a timing advantage. Each of these areas is discussed individually.

Financial Analysts Forecasts and Interim Earnings

Previous studies comparing various forecasts in a capital market context have typically either: 1) not incorporated financial analyst forecasts, or 2) not incorporated abnormal returns for interim periods.

The present study therefore incorporates a very broad set of statistical model forecasts, financial analyst forecasts and capital market results for interim earnings. The present section reviews the relevant aspects of several major publications in this area of research.

The studies of Bathke and Lorek [1984], Brown and Kennelly [1972] and Foster [1977] showed, among other things, that different expectation models provide forecast errors with varying degrees of association with risk-adjusted returns. However, none of these studies included forecasts made by financial analysts which, as cited above, have been shown to produce the most accurate forecasts. The present study includes this source of forecasts.

Also of importance is the Fried and Givoly [1982] study which compared association between abnormal returns and annual forecast errors from both statistical models and financial analysts. Their study included forecasts from Standard and Poor's Earnings Forecaster (financial analysts) and two statistical models: a variation on the Ball and Brown [1968] index model and a random walk model with drift. Their overall results (p. 97) indicated correlations between abnormal returns and annual forecast errors to be .33 for the analysts and .27 for the two statistical models. The authors noted, however, that their results have limited generality. First, they only considered firms for which at least four contemporaneous forecasts were available in the Earnings Forecaster. They noted that this led to exclusion of firms to which relatively less attention was given by analysts. Second they considered only two time series models, both of which do not exploit interim earnings information, whereas the analysts are able to use this information. This is important since Hopwood, McKeown and Newbold

[1982] found that disaggregated interim earnings have more information than the annual earnings alone. The present study therefore extends previous research and uses individual financial analyst forecasts and statistical models that exploit interim earnings for purposes of forecasting annual earnings.

An additional limitation of the Fried and Givoly [1982] study is that it focused on annual as opposed to interim earnings as the object of prediction. The present study therefore, provides evidence on the additional object of prediction, interim earnings. Also (as discussed in detail below) the present research presents market-based evidence on the relative ability of statistical models versus financial analysts to uniquely explain risk-adjusted returns.

A final limitation of the previous literature, regarding the measuring of forecasting accuracy, is that many studies have not controlled for timing advantages pertinent to analyst forecasts. In particular, analyst forecasts are released throughout the entire period and sometimes right before the announcement of the earnings being forecasted. It should be no surprise that forecasts released relatively close to the announcement date are more accurate than those generated by statistical models that generate forecasts made from different base points in time.

Methodological Refinements

The methodology of the present study parallels that of Fried and Givoly ([1982], hence-forth FG) in evaluating the association between statistical model forecasts (versus financial analyst forecasts) of annual earnings per share and risk-adjusted security returns. However, the present study incorporates a number of methodological refinements.

First, it utilizes the actual announcement dates of the firms' earnings in computing the abnormal returns. FG used the more restrictive assumption that earnings for all firms were announced at the end of February.

Second, the present study uses Spearman correlations to avoid distributional problems. FG cited the investigation of Beaver, Clark and Wright [1979] as justification for using the correlation coefficient as a measure of association between forecast error and abnormal return. However, they used the Pearson correlation whereas Beaver, Clark and Wright investigated only the use of the Spearman correlation. This difference is important because it is well known that forecast error distributions based on percentage accuracy metrics are nonnormal and highly skewed.

Third, the present study uses a market-based methodology to directly assess the unique ability of different models to surrogate the market expectation. FG did not directly address this question. (It appears that they were primarily interested in addressing a different question, as discussed below.) This contrasts to the FG study in that they computed the following set of partial correlations:

(A) $R(E, FAF \mid MSM)$

(B) $R(E, FAF \mid IM)$

(C) $R(E, FAF \mid MSM, IM)$

(D) $R(E, MSM \mid FAF)$

(E) $R(E, IM \mid FAF)$

where E denotes the realized earnings, FAF, IM and MSM denote forecasted earnings for the financial analysts, index model and modified submartingale models respectively. Their data indicated that (A), (B)

and (C) were all nonzero while (D) and (E) were typically not different from zero. This led them to conclude (p. 100) that analysts use autonomous information and also fully exploit the time-series and cross sectional properties of the earnings series that are captured by the MSM and IM.

We note that these partial correlation tests relate only indirectly to the surrogation issue for market expectations, since risk-adjusted returns are not included. Furthermore, ranking models based on the bivariate correlation between their forecasts and realized earnings can possibly be misleading if the forecasts are biased. An example of this problem can be seen from the hypothetical situation where a forecast method results in forecasts exactly double the realized earnings. If this occurs for all firms in a given year, there will be a correlation of 1, but this forecast method clearly would not be preferred to a method that had a correlation of .9, but with no bias. Of course, if the bias of the former method is stable over time, one could adjust the forecasts by dividing by two. If this were possible, the former method would be preferred. However, we note that FG made such adjustments (p. 92) without any reduction in forecast error, thus indicating a possible lack of stability in bias over time. In conclusion, the unresolved bias problem provides an additional motivation for investigating the surrogation issue in a market context.

Timing Advantage

As previously discussed, financial analysts have a potential timing advantage over statistical models (henceforth SM's). SM forecasts are effectively made based on information up to and including the most recent earnings announcement. For example, consider a forecast of the

third quarter's earnings made one quarter into the future. A model that uses interim earnings will incorporate the second quarter's earnings. Therefore, this forecast is effectively made at the time of the second quarter's earnings announcement.

In the present example, the analysts' timing advantage arises because the analysts' forecast will typically be made <u>after</u> the second quarter's announcement. In fact the analysts' forecast might even be released within a couple of weeks of the third quarter's earnings release. The present study investigates the impact of this timing advantage on forecast accuracy by explicitly considering (in terms of the present example) the number of days of timing advantage.

Statistical Expectations Models

The present study uses a broad set of 18 statistical expectation models (discussed in a separate section) that forecast both interim and annual earnings. This broad set of models removes at least three limitations found in previous literature. First, as discussed above, models forecasting interim earnings serve as a basis for comparing interim forecasts of financial analysts versus statistical models within a capital market context. Second, the incorporation of interim earnings into the model forecasting annual earnings allows the statistical model access to a broader information set than used by studies (e.g., FG) incorporating only annual data. This is important because, as stated above, interim data can improve forecast accuracy for annual earnings (Hopwood, McKeown and Newbold [1982]). Third, the present study uses multivariate time-series models which can incorporate market information and simultaneously exploit the time series properties of the earnings series.

MODELS PREVIOUSLY USED IN THE LITERATURE

Earnings expectation models can be classified as univariate and multivariate. The term multivariate is used to include models which consider the structural relationship between two or more variables. In addition these models can be further classified as to those based solely on annual data versus those based on quarterly data, producing a total of four categories of models. Each of these categories is discussed individually.

Multivariate Models Using Annual Data

These include the model of Ball and Brown [1968] who regressed an index of annual market earnings changes against the annual earnings changes of individual firms. This model is of the form:

$$(1) \quad (y_t - y_{t-1}) = \alpha + \hat{\beta}(x_t - x_{t-1}) + e_t$$

where y_t represents the annual earnings of the firm, x_t represents a market-wide earnings index, and t is a time subscript denoting a particular year. Also, $\hat{\alpha}$ and $\hat{\beta}$ are estimated using historical data.

Multivariate Models Using Quarterly Data

Similarly, Brown and Kennelly [1972] used the same model as Ball and Brown but applied it to quarterly, instead of annual, data. Henceforth, these will be referred to as the BB and BK models.[2]

A priori, both the BB and BK models have the advantage of defining expected earnings relative to the market's earnings. This type of expectation eliminates the effect of market fluctuations on the individual firm expectations. As long as a firm maintains a constant earnings relation to the market from period to period, unexpected earnings will be zero.

On the other hand, neither of these models explicitly models earnings performance of a firm relative to previous performance for the same firm. In other words, the times-series properties of earnings are not explicitly modeled. The BK model also ignores the fact that firm earnings are seasonally autocorrelated and therefore is likely to have a problem of seasonally autocorrelated residuals.

To address these and other problems Hopwood and McKeown [1981] introduced two single input transfer function-noise models (henceforth HM1 and HM2) which, within a bivariate time-series context, structurally relate a market index of earnings to the individual firm's earnings. The two models are of the form:

$$(2) \quad y_t - y_{t-4} = \theta_0 + \omega_0 (x_t - x_{t-4}) + \phi_1 \omega_{t-1} + \theta_4 a_{t-4} + a_t$$

$$(3) \quad y_t - y_{t-4} = \theta_0 + \omega_0 (x_t - x_{t-4}) + \theta_4 \omega_0 [(x_t - x_{t-4}) - (x_{t-1} - x_{t-5})] + \phi_1 \eta_{t-1} + \theta_4 a_{t-4} + a_t$$

where y_t denotes quarterly earnings per share (adjusted for stock splits and dividends), x_t denotes an index of market earnings, $[\theta_i, \omega_0, \phi_1]$ are model parameters, a_t is an uncorrelated residual series, and η_t a noise series or the error from the transfer function part of the model.

<u>Actual versus Forecasted Index Models</u>

Note that all of the multivariate models (i.e., HM1, HM2, BK and BB) can be based on either a forecasted or actual index. We have therefore also considered the HM1F, HM2F, BKF and BBF models which are based on forecasts of the index series, where an individually identified BJ model is applied to the index series. Henceforth we shall refer to

the latter type of models as FI (Forecasted Index) models, and the HM1, HM2, BK and BB models as AI (Actual Index) models.

The question arises as to whether the AI or FI models are the more appropriate models for investigation. One might argue that AI model forecasts are not really forecasts at all since they rely on knowing an index value not observable until the same period to which the forecast relates. Nevertheless, this use of the term "forecast" is well entrenched in the literature and as such is used in the present research. The present study evaluates both AI and FI forecasts; however, only AI results are presented. As noted below, this did not affect any of the conclusions.

Univariate Models Using Quarterly Data

Unlike the bivariate regression models, univariate models ignore the firm's relation to the market (or other indicators) but explicitly model the time-series properties of the earnings number. Collins and Hopwood [1980] studied the major univariate time-series models found in recent literature. These include: (1) a consecutively and seasonally differenced first order moving average and seasonal moving average model (Griffin [1977] and Watts [1975]), (2) a seasonally differenced first order auto-regressive model with a constant drift term (Foster [1977]), and (3) a seasonally differenced first order auto-regressive and seasonal moving average model (Brown and Rozeff [1978, 1979]). In the Box and Jenkins terminology, these models are designated as (0,1,1) x (0,1,1), (1,0,0) x (0,1,0) and (1,0,0) x (0,1,1) respectively. In this study, they are referred to as the GW, F, and BR models. Collins and Hopwood [1980] found that the BR and GW models produced annual forecasts which were more accurate than the F model. In addition, they concluded

that they also did at least as well as the more costly individually-identified Box-Jenkins (BJ) models. Most important, they found the analyst forecasts significantly more accurate than any of the univariate models examined.

Univariate Models Using Annual Data

The results of a large number of studies provide a substantial amount of evidence that annual earnings follow a random walk (henceforth RW) or a random walk with a drift. Support for this conclusion comes from Ball and Watts [1972], Beaver [1970], Brealey [1969], Little and Rayner [1965], Lookabill [1976] and Salamon and Smith [1977]. In addition, Albrecht et al. [1977] and Watts and Leftwich [1977] found that full Box-Jenkins analysis of individual series did not provide more accurate forecasts than those of the random walk or random walk with drift.

Synthesis

The above models are summarized in Figure 1.

Figure 1

Structure:	Data Used for Estimation: Annual	Data Used for Estimation: Quarterly
Univariate	BJ RW-Drift I	BR GW F BJ II
Multivariate	BB III	HM1 HM2 BK IV

Previous research has focused on comparing models within Category II (e.g., Collins and Hopwood [1980] and Brown and Rozeff [1979]), within Category I (e.g., Watts and Leftwich [1977]), or between Categories II and IV (Hopwood and McKeown [1981]). Relatively little attention has been devoted to comparing models between (I, III) and (II,IV), in spite of the fact that models in both of these sets have been used to forecast the same objective, annual earnings. The present research investigates all four categories[3] (and in addition, financial analyst forecasts), thereby providing a unified framework for model evaluation.

ANNUAL FORECAST RESULTS

Sample

The sample in this study includes all firms which met the following criteria:

1. Quarterly earnings available on Compustat for all quarters for the period 1962-1978 with fiscal year ending in December for each year in that period.
2. Value Line Investment Survey forecasts available from the period 1974-1978.[4]
3. Monthly market returns available on the CRSP tape from 1970 through 1978.

These restrictions resulted in a sample of 258 firms.[5]

The first criterion assured that a sufficient number of observations (17 years or 68 quarters) were available for time series modeling. Based upon the Box-Jenkins [1970] rule of thumb requiring approximately 50 observations, 20 time-series models were estimated for each firm based on 48, 49, ..., 67 observations. In other words, the first model estimation used data for the 48 quarters beginning at the

first quarter of 1962 and ending with the 4th quarter of 1973. The next model incorporated data from the first quarter of 1962 through the first quarter of 1974.

The Value Line forecasts used in the present study represent point forecasts of earnings made by individual analysts (as opposed to consensus forecasts). These forecasts are updated quarterly. Therefore, in each year analyst forecasts are made four times: The first forecast is made after the previous year's earnings are reported, but prior to the release of the first quarter's earnings; the second forecast is made subsequent to the release of the first quarter's earnings, but prior to the release of the second quarter's earnings; and so on. Furthermore, analyst forecasts are made for periods varying 1, 2, 3, and 4 quarters into the future. Therefore, annual earnings forecasts used in this research are based on the sum of past realizations plus the sum of forecasts for the remainder of the year. Specifically, the first annual earnings forecast is the sum of forecasts for the first through fourth interim periods, where these forecasts are all made at a point in time after the release of the prior year's earnings, but prior to the release of the first quarter's earnings in the current year. The second annual earnings forecast is the first quarter's reported earnings plus the sum of the forecasts for the second through fourth interim periods, where these forecasts are made at a point in time subsequent to the release of the first quarter's earnings, but prior to the release of the second quarter's earnings. The third annual earnings forecast is the sum of the first and second quarter's reported earnings plus forecasts for the third and fourth quarters, where these forecast are made at a point in time between the release of

the second and third quarter's earnings. Finally, the fourth annual earnings forecast is the sum of the reported earnings for the first three quarters plus a forecast of the fourth quarter's earnings, where this forecast is made at a point in time between the release of the third and fourth quarters' earnings.

Application of the Models to the Capital Market

The market model of the form:

$$(4) \quad E[\ln(1 + R_{it} - R_{ft})] = \alpha_i + \beta_j \ln(1 + R_{mt} - R_{ft})$$

was estimated, where (4) is the log form of the Sharp-Lintner [Lintner, 1965] capital asset pricing model[6], R_{it} represents the return on asset i in period t, R_{mt} represents the return on a value-weighted market index in period t, and R_{ft} is the risk free (treasury bill) rate of return in period t. The estimation of α_i and β_i was done using ordinary least squares regression for each year in the hold-out period. The estimations were performed in each case by including monthly data for the 5 years preceding the hold-out year. The sum of the residuals (post-sample forecast errors) from these models when applied to the hold-out years (the twelve months up to and including the annual earnings announcement date) constitute risk-adjusted abnormal returns. The market index used was the value-weighted market index containing dividend and price returns as supplied on the CRSP tape.[7]

The next phase was to estimate the association between the unexpected annual earnings from the earnings expectation models and the annual cumulative abnormal returns (CAR's). (These were computed by adding the monthly abnormal returns.) This approach was outlined by Foster [1977, p. 13]:

> This analysis examines whether there is an association between unexpected earnings changes and relative risk adjusted security returns. Given a maintained hypothesis of an efficient market, the strength of the association is dependent on how accurately each expectation model captures the market's expectation.....

Foster applied this approach assuming a long investment given that the unexpected earnings number was positive and a short investment given that it was negative. He then proceeded to measure the abnormal returns for different forecast methods given this investment strategy.

Subsequent to Foster's research, Beaver, Clarke and Wright [1979] showed that the magnitude of the unexpected earnings is an important determinant of the size of the associated abnormal return (also see Joy et al. [1977]). Furthermore, these empirical results were supported by the analytical work of Ohlson [1978]. We therefore measured association via Spearman's rank correlation between the scaled ((Actual - Predicted)/|Predicted|) unexpected earnings of the individual models and the residuals (annual CAR) and averaged these results across 5 hold-out years.

Forecast Accuracy Results

Forecast accuracy results were computed, based on mean absolute relative errors for all of the models discussed above. For each quarterly model the mean annual errors are given for forecasts made 4, 3, 2 and 1 quarters prior to year end. For 4 quarters prior to year end, the annual forecast is the sum of the forecasts for each of the interim periods. For 3 quarters prior to year end, the annual forecast is the actual first quarter earnings plus forecasts of the second, third and fourth quarters' earnings. Therefore, realizations were substituted for forecasts as the end of the year approached. Also, all of the statistical forecast models were reestimated and reidentified as new quarters of earnings became available.

Due to the large number of statistical models evaluated (and the consequent volume of data), subsequent sections report only a subset of the models investigated. However, the result of the omitted models, in terms of the hypotheses tested, are similar and do not affect any of the conclusions. The choice of the models to be reported was based on those most commonly found in the literature.

Table 1 gives the forecast errors, based on the mean absolute relative error, defined as the average of |(actual-predicted)/(actual)|. Each column represents errors for different quarters relative to year end. Note in column 1 (which represents four quarter ahead annual forecast errors) that the financial analyst forecasts are most accurate. This superior forecast accuracy is consistent with many other studies (e.g., Brown and Rozeff [1978]) and is therefore no surprise. Therefore these data simply confirm that our sample does not differ substantially in this respect from other studies. We also note that among the time series models using quarterly data, the HM1 model has the lowest average error for four quarter ahead forecasts. However, it is also important to note that the difference between the best and worst of these models is fairly small. Also it appears (consistent with Collins and Hopwood [1980]) that the differences between all forecast methods remains small as the year end approaches.

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TABLE 1 ABOUT HERE

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Capital Market Results

Column 1 of Table 2 (labeled Bivariate) gives the rank correlations (as defined above) between forecast errors and abnormal returns. Each forecast method is associated with 2 lines of data. The first line gives the rank

correlation and the second line the associated t values for the null hypothesis of a zero correlation.[8] Note that the analysts have the highest association (.3659).

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TABLE 2 ABOUT HERE

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Column 2 of Table 2 (labeled Partial Out Analyst) gives the rank correlations between risk adjusted returns and model errors with the analyst errors held constant. This shows that the model forecast errors have a consistent pattern of association with abnormal return beyond that which is explained by the analyst forecast errors. Similarly, Column 3 (labeled Partial Out Model) strongly indicates that the analyst errors have a significant association with abnormal returns even when the corresponding model's errors are partialled out. The last 3 columns of Table 2 give the number of years, out of five, that the indicated correlations (on an individual-year basis) are significant. For example (from column 4), the bivariate association between risk-adjusted returns and the Griffin-Watts (GW) forecast errors is significant in all 5 years. The association (column 5) between GW forecast errors and risk adjusted returns (with analyst forecast errors held constant) is significant in 3 out of the 5 years. Finally (from column 6) the association between the financial analyst forecast errors and risk-adjusted returns (with GW forecast errors held constant) is significant in all 5 years.

Rank Correlations Between Actual Earnings and Forecasts

Table 3 present results comparable to those in Table 2, but using actual earnings instead of abnormal returns, and forecasted earnings instead of forecast errors. We present these numbers for comparability to Fried and

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TABLE 3 ABOUT HERE

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Givoly [1982], though, as discussed above, there are limitations to their interpretation. The most significant aspect of this analysis is Column 2 which indicates that forecasts from all of the models appear to have significant explanatory power beyond the analyst forecasts. Note that these results are consistent with the capital market results reported in Table 2. In this case their implication is that, for purposes of forecasting earnings, the statistical models exploit information that is not exploited by financial analysts.

QUARTERLY FORECAST RESULTS

Tables 4 through 6 are direct analogs of tables 1 through 3, but are based on quarterly (as opposed to annual) forecasts.[9] Table 4 gives forecast errors for forecast horizons extending 1, 2, 3 and 4 quarters into the future. Table 5 gives correlations between forecast errors and CAR. Finally, Table 6 gives correlations between forecasts and reported earnings.

Overall, the quarterly forecast error results here are similar to the annual results reported in the previous section. In Table 4, the analysts consistently produce the most accurate forecasts. For example, for one quarter ahead forecasts the average analyst error is .2804 while the next best average is .3450 for the HM2 model. In summary, these results are consistent with previous literature supporting superiority of analyst forecasts.

Column 1 of Table 5 indicates a consistent pattern of significant association between the forecast errors of all forecast methods and CAR. Note, however, that a number of the statistical models have forecast errors with higher associations than the analyst forecast errors. Therefore these

data do not support the hypothesis that financial analyst forecast errors are more highly associated than statistical model forecast errors with risk-adjusted security returns. Column 2 of table 5 reports the correlation between the statistical model forecast error and CAR after controlling for the financial analyst forecast error. These data indicate for the large part that the statistical models do retain incremental association with CAR, even after controlling for the analyst forecast error. This conclusion is supported by column 5 which reports, for example, that the GW model has significant (alpha=.05, one tailed) t-values in 14 out of the 20 quarters (on an individual period basis).

Column 3 presents the correlations between analyst forecast errors and CAR with the model forecast errors partialled out. These data indicate an overall pattern of significance, and, as indicated in column 6, there are many cases where the t-values for individual quarters are significant. For example, for the GW model this t-value is significant at alpha=.05 in 9 out of the 20 quarters.

In conclusion, Table 5 is consistent with the hypothesis that the analyst forecasts do not uniquely capture the market's expectations for interim earnings. Furthermore, the significant partial correlations in column 2 of table 5 are supportive of the hypothesis that the statistical model forecasts have incremental explanatory power relative to analyst forecasts in terms of explaining CAR.

Table 6 presents results similar to Table 5, but forecasts are correlated with actual earnings. As expected, column 1 of table 6 shows that forecasts and earnings are highly correlated. However, note that the partial correlations in column 2 are significant. This is supported by column 5 which, for example, indicates that the t-values are significant (alpha=.05)

for the GW model in 18 out of the 20 quarters. Therefore these data are consistent with the hypothesis that the analyst forecasts do not fully exploit the time-series-information processed by the statistical models. Similarly,

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TABLES 4 THROUGH 6 ABOUT HERE

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the results of column 3 of Table 6 support the hypothesis that the time-series models do not fully exploit the information available to the analysts.

Timing Advantage Hypothesis

The present section investigates the hypothesis that the advantage of analysts over statistical models is due to a timing advantage. Such a possibility arises because analysts typically make their forecasts closer to the announcement date of the target earnings than do the statistical models. Consider, for example, forecasts of the second quarter's earnings. The statistical models rely on the first and previous quarters' earnings and are therefore effectively made from the date that the first quarter's earnings are announced (although using information covering only the time through the end of the first quarter). However, in this case the analyst forecast will often be made weeks later. Therefore, there exists the possibility that the findings of "superiority" in favor of the analysts can be accounted for by this timing advantage (based on the analysts' potential opportunity to observe relevant economic events in the second quarter before making the forecast). Note that Table 1 provides implicit evidence of this phenomenon, where the statistical model forecasts are more accurate than the financial analysts when the model forecasts are based on more recent information. For example, all of the statistical model forecasts made beginning quarter 2 are on the average

more accurate than the financial analyst forecasts made beginning with the first quarter.

To test for a timing advantage, we first investigate the correlation between the difference ≡ (BJ absolute relative forecast error - Analyst absolute relative forecast error) and the number of days separating these two forecasts.[10] If there is an analyst timing advantage, this correlation should have a tendency to be positive in each of the 20 quarters of our data sample. In other words, we would expect that a larger number of days separating the analyst forecast from the model forecast would be associated with a larger timing advantage. Table 7 presents this correlation statistic for each of the 20 quarters over the sample period. Note that the correlations are positive in all 20 quarters. Under the null hypothesis of no timing advantage, a simple sign test rejects the null hypothesis at the .01 level. Furthermore, the individual correlations are significant at the .05 level in 12 cases. Overall, Table 7 is supportive of a timing advantage contributing to the superior forecast accuracy of financial analysts.

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INSERT TABLE 7 ABOUT HERE

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To further investigate the timing advantage hypothesis and to provide an alternative statistical approach, we also partition the quarterly forecast accuracy results based on the number of days of timing advantage. Table 8 gives these results for 5 separate equal sample size partitions.[11] (Appendix A gives specifics on the timing advantages associated with each partition.) The first partition includes cases where the analyst timing advantage is the least. Going from partition 1 to partition 5, the timing advantage increases and is largest in partition 5. Partition 1 reveals that, in contrast to the

sample as a whole, the analyst forecasts are no longer the most accurate after controlling for the timing advantage. Note that in the one-quarter-ahead case the analyst forecasts are no more accurate than those of the two HM models. Furthermore, in the four quarter ahead case the analyst forecasts are not more accurate than any of the model forecasts. Note on the other hand in partition 5, where the analyst timing advantage is at a maximum, that the analyst forecast errors are consistently smaller than those of all models. This is true for all forecast horizons, ranging from one to four quarters into the future.

Summary and Conclusions

This study investigated the use of statistical model forecasts versus financial analyst forecasts as surrogates of capital market expectations for both interim and annual earnings per share. In addition, extensions to previous research were made by incorporating fairly broad sampling constraints, including a very general set of statistical models, making certain methodological refinements, and controlling for the impact of financial analysts' timing advantages on forecast accuracy.

The empirical results for annual earnings indicated that the financial analyst forecast errors were more highly associated with risk-adjusted security returns than the forecast errors of statistical models. In addition, the partial correlations between analyst errors (controlling for the statistical model forecast errors) and risk-adjusted security returns were generally non-zero. The partial correlations between the statistical model forecast errors (controlling for the analyst forecast error) and risk-adjusted security returns were also statistically significantly different from zero. These data are consistent with the hypothesis that, in a capital market context, the analyst forecasts more closely approximate the market's

expectation for annual earnings. However, the non-zero partials are consistent with the hypothesis that neither the financial analysts nor the statistical models uniquely (relative to each other) explain risk-adjusted security returns.

Similar tests were conducted for models that forecast interim earnings. Unlike models forecasting annual earnings, a number of models forecasting interim earnings produced forecast errors that exhibited a higher association with risk-adjusted security returns than did financial analyst forecast errors. Both sets of partial correlations described in the previous paragraph were non-zero. The data indicate that the partial correlations between risk adjusted security returns and statistical model forecasts (controlling for the analyst forecast error) were typically non-zero. These data are consistent with the hypothesis that analyst forecasts do not uniquely surrogate for the market's expectation of interim earnings.

We also investigated the association between earnings and forecasts. In both cases the partial correlations between statistical model forecasts and reported earnings were usually non-zero. These data are consistent with the hypothesis that the financial analysts do not fully exploit the information contained in the time series of previous earnings data.

Finally, the empirical forecast accuracy results were consistent with previous literature. Overall the financial analysts produced the most accurate forecasts. This was true for both interim and annual forecast errors. However, after controlling for the timing advantage, the analyst forecasts were no longer the most accurate.

Table 1

Mean Absolute Relative Error
(Truncated at 1)

Model	Annual Forecasts Beginning With Quarter 1	2	3	4
Griffin-Watts	.2679	.2149	.1543	.1047
Foster	.2651	.2183	.1642	.1147
Brown-Rozeff	.2640	.2150	.1502	.1053
Box-Jenkins	.2654	.2224	.1560	.1021
Hopwood-McKeown 1	.2606	.2059	.1521	.1041
Hopwood-McKeown 2	.2623	.2142	.1514	.1026
Analyst	.2248	.1845	.1359	.0780
Ball-Brown	.5173			
Random Walk	.2610			

Table 2

Rank Correlations of Annual Forecast Error with CAR

	Correlation Values*			Number of years significant at 5% (out of 5)		
	1	2	3	4	5	6
		Partial Out			Partial Out	
Model	Bivariate	Analyst	Model	Bivariate	Analyst	Model
Griffin-Watts	.2908 10.4830**	.1205 4.1873	.2601 9.2897	5	3	5
Foster	.2860 10.2974	.1009 3.4955	.2575 9.1901	5	2	5
Brown-Rozeff	.2855 10.2780	.0868 3.0033	.2532 9.0255	5	0	5
Box-Jenkins	.2743 9.8401	.0745 2.5746	.2620 9.3597	5	1	5
Hopwood-McKeown 1	.2611 9.3322	.0414 1.4299	.2685 9.6128	4	3	5
Hopwood-McKeown 2	.2645 9.4599	.0402 1.3869	.2651 9.4802	5	1	5
Ball-Brown	.0475 1.6411	-.1035 -3.5885	.3758 13.9843	1	0	5
Random Walk	.3075 11.1472	.0608 2.1014	.2168 7.6579	4	2	5
Analyst	.3659 13.5639			5		

*The correlations in columns 1 through 3 are based on pooling of the 5 years. Columns 4 through 6 give the number of individual-year (out of 5) correlations that are significant at $\alpha = .05$.

**The second line for each model reports the associated t statistics.

Table 3

Rank Correlations of Annual Forecast with Actual Annual EPS

Model	Correlation Values* 1 Bivariate	2 Partial Out Analyst	3 Partial Out Model	Number of years significant at 5% (out of 5) 4 Bivariate	5 Partial Out Analyst	6 Partial Out Model
Griffin-Watts	.7228 36.0830**	.2603 9.2959	.3936 14.7642	5	3	5
Foster	.7139 35.1648	.2144 7.5680	.3973 14.9299	5	3	5
Brown-Rozeff	.7203 35.8231	.2329 8.2580	.3861 14.4348	5	4	5
Box-Jenkins	.7077 34.5507	.1993 7.0116	.4090 15.4566	5	4	5
Hopwood-McKeown 1	.7114 34.9219	.1918 6.7393	.3947 14.8106	5	3	5
Hopwood-McKeown 2	.7220 35.9937	.2121 7.4824	.3695 13.7104	5	4	5
Ball-Brown	.2954 10.6674	.0810 2.8029	.7272 36.531	5	3	5
Random Walk	.7018 33.9879	.1063 3.6859	.3957 14.8556	5	2	5
Analyst	.7531 39.4848			5		

*The correlations in columns 1 through 3 are based on pooling of the 5 years. Columns 4 through 6 give the number of individual-year (out of 5) correlations that are significant at $\alpha = .05$.

**The second line for each model reports the associated t statistics.

Table 4

Mean Absolute Relative Quarterly Forecast Errors
(Truncated at 3)

Model	Forecast Horizon 1	2	3	4
Griffin-Watts	.3548	.4117	.4439	.4723
Foster	.3700	.4290	.4515	.4762
Brown-Rozeff	.3402	.3909	.4207	.4394
Box-Jenkins	.3614	.4040	.4243	.4435
Hopwood-McKeown 1	.3484	.4033	.4279	.4430
Hopwood-McKeown 2	.3450	.3946	.4250	.4382
Analyst	.2804	.3669	.3978	.4336

Table 5

Rank Correlations of Quarterly Forecast Error with CAR

	Correlation Values*			Number of quarters significant at 5% (out of 20)		
	1	2	3	4	5	6
		Partial Out			Partial Out	
Model	Bivariate	Analyst	Model	Bivariate	Analyst	Model
Griffin-Watts	.1829 13.1003**	.1157 8.1978	.0848 5.9886	17	14	9
Foster	.2081 14.9762	.1462 10.4048	.0716 5.0503	18	16	8
Brown-Rozeff	.1506 10.7247	.0762 5.3766	.1030 7.2860	17	7	9
Box-Jenkins	.1634 11.6584	.0930 6.5725	.0968 6.8434	16	11	9
Hopwood-McKeown 1	.1745 12.4732	.1019 7.2072	.0853 6.0258	17	10	8
Hopwood-McKeown 2	.1564 11.1485	.0802 5.6663	.0971 6.8672	16	10	8
Analyst	.1655 11.8161			17		

*The correlations in columns 1 through 3 are based on pooling of the 20 quarters. Columns 4 through 6 give the number of individual-quarter (out of 20) correlations that are significant at $\alpha = .05$.

**The second line for each model reports the associated t statistics.

Table 6

Rank Correlations of Quarterly Forecast with Actual Quarterly EPS

	Correlation Values*			Number of quarters significant at 5% (out of 20)		
	1	2	3	4	5	6
		Partial Out			Partial Out	
Model	Bivariate	Analyst	Model	Bivariate	Analyst	Model
Griffin-Watts	.7902 91.0834**	.2544 18.5836	.6114 54.5773	20	18	20
Foster	.7775 87.3436	.2209 16.0007	.6286 57.0925	20	18	20
Brown-Rozeff	.7998 94.1443	.2628 19.2386	.5917 51.8465	20	20	20
Box-Jenkins	.7631 83.4163	.1943 13.9927	.6485 60.1874	20	18	20
Hopwood-McKeown 1	.7930 91.9492	.2456 17.8946	.6028 53.3635	20	18	20
Hopwood-McKeown 2	.7954 92.7224	.2383 17.3312	.5951 52.3099	20	17	20
Analyst	.8652 121.8780			20		

*The correlations in columns 1 through 3 are based on pooling of the 20 quarters. Columns 4 through 6 give the number of individual-quarter (out of 20) correlations that are significant at $\alpha = .05$.

**The second line for each model reports the associated t statistics.

Table 7

Spearman Correlations Between Analyst Forecast Superiority*
and the Number of Days Separating the Two Forecasts
(Quarterly Forecasts)

Quarter	Number of Observations	Correlation	Alpha Level
1	136	.1644	.028
2	173	.0348	.325
3	172	.1910	.007
4	163	.0147	.427
5	145	.0671	.212
6	175	.1213	.055
7	174	.2842	.001
8	172	.2237	.002
9	168	.1527	.025
10	171	.1780	.010
11	168	.1303	.047
12	167	.1425	.034
13	159	.1332	.048
14	170	.0173	.412
15	174	.0826	.140
16	174	.1309	.043
17	167	.1405	.036
18	170	.0918	.118
19	170	.2135	.003
20	162	.0883	.132

*Analyst Forecast Superiority is defined as:

$$\frac{|\text{Actual EPS} - \text{Analyst Forecast}|}{|\text{Actual EPS}|} - \frac{|\text{Actual EPS} - \text{BJ Forecast}|}{|\text{Actual EPS}|}$$

Table 8

Mean Absolute Relative Quarterly Forecast Errors
(Truncated at 3)

Model	Forecast Horizon 1	2	3	4
	Partition 1 (minimum analyst advantage)			
Griffin-Watts	.2816	.2965	.3330	.3308
Box-Jenkins	.2841	.2900	.3136	.3057
Hopwood-McKeown 1	.2706	.2778	.3030	.3083
Hopwood-McKeown 2	.2661	.2705	.2996	.2978
Analyst	.2781	.2915	.3244	.3685
	Partition 2			
Griffin-Watts	.3137	.3690	.4073	.3903
Box-Jenkins	.3150*	.3702*	.3781	.3830
Hopwood-McKeown 1	.3157	.3596	.3911	.3890
Hopwood-McKeown 2	.3051	.3547	.3843	.3681
Analyst	.2754	.3369	.3840	.3870
	Partition 3			
Griffin-Watts	.3935*	.4557*	.4991	.5792
Box-Jenkins	.4063*	.4382*	.4988*	.5771*
Hopwood-McKeown 1	.3643*	.4280	.4708	.5582
Hopwood-McKeown 2	.3618*	.4247*	.4660	.5649*
Analyst	.3091	.4137	.4510	.5286
	Partition 4			
Griffin-Watts	.4487*	.5227*	.5830*	.5605*
Box-Jenkins	.4360*	.5000*	.5280*	.4975*
Hopwood-McKeown 1	.4549*	.5222	.5610*	.5178*
Hopwood-McKeown 2	.4567*	.5230*	.5726*	.5305*
Analyst	.3297	.4182	.4771	.4414
	Partition 5 (maximum analyst advantage)			
Griffin-Watts	.3370*	.3962*	.4159*	.4429*
Box-Jenkins	.3390*	.3889*	.4072*	.4390*
Hopwood-McKeown 1	.3178*	.3820*	.4044*	.4112
Hopwood-McKeown 2	.3203*	.3750*	.4120*	.4014
Analyst	.2313	.3230	.3314	.3631

*Significantly different from financial analyst error at $\alpha = .05$.

Appendix A

Maximum Number of Days of Analyst Timing
Advantage* in Each Partition

Quarter	Partition 1	2	3	4	5
1	9	18	25	57	92
2	14	22	38	72	94
3	11	18	37	65	98
4	18	36	64	91	134
5	9	15	25	51	92
6	15	21	36	70	95
7	14	18	37	67	94
8	11	18	35	65	92
9	4	14	28	65	88
10	11	22	46	74	95
11	9	17	43	74	99
12	11	25	59	80	130
13	8	22	52	71	87
14	9	30	56	74	95
15	11	32	60	74	95
16	11	36	60	74	105
17	3	21	56	71	120
18	14	32	60	77	94
19	11	35	64	77	163
20	16	36	60	78	106

*Analyst Timing Advantage ≡ days elapsed between previous quarter's earnings announcement and publication of analyst forecast

NOTES

[1]Brown et al. [1985, 1986] provide some evidence in support of a timing advantage. Our analysis is not so much concerned with whether such an advantage exists, but rather whether the analysts outperform statistical models given control for timing. Our analysis differs in other important ways, including the set of statistical models considered and our incorporation of earnings release dates for purposes of measuring timing advantage.

[2]We use these and other abbreviations for convenience and do not wish to imply that the authors necessarily advocated the general use of these models.

[3]We do not include the category I BJ model, since Box and Jenkins [1970] suggest that a minimum of 50 observations be used in the modeling process. We were unable to obtain annual series that met all of our sampling constraints and approached this recommended minimum number of observations. Even if the data were available, models incorporating half of a century's data would be problematic due to structural changes in the economy.

[4]We did not delete firms with some missing Value Line data since there were a considerable number of firms where only one number was unavailable. However, this had virtually no effect on our overall sample size since the percentage of missing data was less than 2%.

[5]These sample constraints apply to our annual analysis. The sampling procedures and capital market analysis were slightly different for the quarterly analysis. Specifically, the quarterly analysis required returns on the daily CRSP tape to compute weekly returns (Tuesday to Tuesday) for the period from the fourth quarter of 1972 through the first quarter of 1979. The resulting sample contained 9 fewer firms (249 in total) than for the annual analysis.

[6]The logarithmic form of the market model is used so the variable being analyzed equals the continuously compounded return. This also allows some appeal to a central limit theorem argument (Fama [1976, p. 20]; Alexander and Francis [1986, p. 145]) concerning normality of the variable.

[7]The procedure to compute quarterly abnormal returns was analogous to that used to compute annual abnormal returns. The log form of the market model (risk free rates of return were generally not available for periods less than one month) with a value-weighted index was used. Regression estimations were done for each holdout quarter (between 1974 and 1978) using OLS regression and in each case including weekly data for the 65 weeks preceding the week containing the first market day of the quarter. The residuals (post sample forecast errors) from these models when applied to the holding periods (the inclusive interval from the week containing the first market day of the quarter to the week containing the announcement date) constitute risk-adjusted returns. The abnormal returns were then individually summed across each holding period to give the firms' cumulative abnormal returns.

[8]The associations in columns 1 through 3 are based on pooling the data across the 5 sample years. Columns 4 through 6 indicate the number of significant individual-year correlations (from a maximum of 5). This same format is followed in subsequent tables.

[9]The associations are pooled across 20 quarters.

[10]This analysis required Value Line forecast publication dates in addition to the other data. Due to resource constraints we collected dates for a subsample of 182 firms. To insure that this procedure had no biasing effect, we ran the forecast error analysis for the subsample and sample as a whole and obtained virtually identical results. Also the choice of the BJ model here is arbitrary. However, followup results (Table 8) indicate a timing effect for all models.

[11]The statistical tests in the various partitions were based on the distribution-free multiple comparison test (using Friedman Rank Sums) for multiple treatments versus a control (Hollander and Wolfe [1973, p. 155]. Note that these tests are not independent; therefore, the focus should be on the pattern of significances across partitions rather than on differences in significances within partitions.

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